

FULL ARTICLE



Impacts of EU funded R&D networks on the generation of key enabling technologies: Empirical evidence from a regional perspective

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Abstract

Cross-regional R&D networks are essential for regional innovativeness. Yet, we lack insights into technology field-specific effects of a region's network connectivity. This study investigates key enabling technologies (KETs) to compare knowledge creation effects of EU funded R&D networks for different technological fields. By applying spatially filtered regression models together with marginal effect interpretations for non-linear models we quantify and compare network effects across KET fields. Results show that the generally positive network effects differ depending on region-internal endowments and the nature of the underlying technologies. Policy implications arise for the interrelations between EU research, industrial and regional policy.

KEYWORDS

R&D networks, key enabling technologies (KETs), regional knowledge production, network embeddedness, interaction effects

1 | INTRODUCTION

Based on a theoretical debate in the first decade of the 21st century, first empirical works have appeared recently to provide empirical evidence on the benefits of collaborative research and development (R&D) for knowledge creation and innovation (Fornahl, Broekel, & Boschma, 2011; Ponds, van Oort, & Frenken, 2010; Varga, Pontikakis, &

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Chorafakis, 2014; Wanzenböck & Piribauer, 2018). These works indeed underline that—as suggested by theory—knowledge-intensive organizations increasingly mobilize non-local collaborations and international networks to access external knowledge over distance for their research and innovation activities. In a similar vein, it is argued at the regional level that a high network interconnectivity enables the inflow of new knowledge via cross-regional collaborations, which in turn stimulates region-internal innovation activities, enriches the local knowledge base, and even supports processes of diversification and technological renewal of entire sectors or regions (e.g., Boschma & Frenken, 2010).

With the aim of leveraging the positive mechanisms associated with such cross-regional R&D collaborations, a number of policy measures have been implemented at the regional, national and supra-national level. The European Framework Programme (FP) is one of the most prominent examples, widely investigated in recent literature (Autant-Bernard, Billand, Frachisse, & Massard, 2007; Scherngell & Barber, 2009; Sebestyen & Varga, 2013; Wanzenböck, Scherngell, & Lata, 2015). A recent contribution of Wanzenböck and Piribauer (2018) provides original evidence on the positive impacts of FP network embeddedness on a region's ability to create new knowledge. While most studies in the field take an aggregated perspective on network effects and regional knowledge creation intensities, we shift in this paper the debate to the questions whether and how EU-wide R&D networks can generate positive impacts in different technological fields. In other words, we are interested in whether the positive impacts of collaborative R&D holds when we investigate specific technologies, and their idiosyncrasies with respect to different modes of knowledge creation, the heterogeneities in the underlying knowledge base or their stage of development. By assuming that such heterogeneities crucially influence the relevance and spatial scale of R&D collaboration, the aim of this paper is to estimate how regional embeddedness in EU funded R&D networks affects regional knowledge creation across different technological fields, and to disentangle potential similarities and differences in terms of estimated network effects between the technologies.

To gain this more fine-grained understanding of the role of the EU funded R&D networks, we focus on the case of key enabling technologies (KETs),¹ which is in a European policy context a particularly interesting case for the investigation of network effects under technological heterogeneity. KETs are considered as generic technologies, which serve as basic technological input for a variety of innovations and in a variety of different industries. Given their horizontal and systemic nature, the opportunities for cross-sectoral and cross-regional spillovers, especially between leading and lagging regions, are as assumed to be high (Montresor & Quatraro, 2017). For regions or countries, the specialization in KETs is therefore often associated with a higher ability to create more sustainable innovation paths, to build linkages across industries and to create new potentials for diversifying into new sectors (European Commission, 2009, 2012, 2015a). In line with the ideas of a new industrial policy approach (Foray, 2016; Rodrik, 2014), one of the current priorities of the EU is to foster research and capability building activities around KETs and to induce industrial change particularly in structurally weak regions. However, the empirical studies of Montresor and Quatraro (2017) and Evangelista, Meliciani, and Vezzani (2018) show that the spatial distribution of KETs is highly concentrated in certain regions in Western and Central Europe with high regional disparities across Europe.

To observe R&D network structures in different KETs, we rely on the definition of the European Commission (European Commission, 2015b). Based on keywords, we identify relevant projects funded by FP7 and construct KET-specific R&D networks at the regional level. Social network analytic (SNA) centrality measures are used to calculate a region's positioning in the field-specific networks. Our regional sample consists of a set of 257 European NUTS 2 regions. The empirical model we are employing is based on the assumption that the resources and skills

¹The six fields under consideration are: (i) Nanotechnology; (ii) Microelectronics; (iii) Photonics; (iv) Advanced materials; (v) Advanced manufacturing technologies; and (vi) Industrial biotechnology. The notion of key enabling technologies (KETs) has been introduced by the EU (Montresor & Quatraro, 2017). From a scientific point of view, the roots of the concepts show similarities with the notion of general purpose technologies (GPT) (Bresnahan & Trajtenberg, 1995; Lipsey, Carlaw, & Bekar, 2005; Qiu & Cantwell, 2018), or emerging technologies (as for biotechnology, for instance, see Rotolo, Hicks, & Martin, 2015). A well-defined framework for KETs, their specific characteristics and demarcation to other related concepts has not been developed yet. However, the study at hand focuses not on the semantic properties of the concept but rather on providing systematic empirical evidence with respect to differing technological fields.



available in a region significantly moderate how external knowledge can be absorbed and utilized. In analogy to the study of Wanzenböck and Piribauer (2018) we control for this conditional relationship between network embeddedness and own region endowments in an augmented regional knowledge production function (KPF) framework.

A methodological advancement of this paper is that we account for the non-linearities in a spatially filtered negative binomial regression model, and introduce adjusted marginal effects interpretations to quantify potential interaction effects, on the one hand, and to compare these effects across KETs, on the other hand. Our results on R&D network effects are consistent with the differentiation into: (i) science-based fields, building on scientific inputs, a more explicit knowledge base and global knowledge transmission patterns; and (ii) application-oriented fields in which practical experience and more localized or informal knowledge exchange process may be prevailing.

This paper is organized as follows. In Section 2, we provide theoretical reasons for studying R&D network effects under the lens of technological heterogeneity, before we present in Section 3 our approach to construct the technology-specific R&D networks and to calculate a region's network embeddedness therein. In Section 4, we introduce our empirical model relating to R&D networks and region-internal endowments to knowledge creation in KETs, and in Section 5, we derive the marginal effect calculations necessary to derive comparable results for the different KET fields. Section 6 discusses the estimation results, before Section 7 concludes in light of the technological heterogeneities observed and provides some implications in a policy context as well as ideas for a future research agenda.

2 | TECHNOLOGICAL HETEROGENEITY OF R&D NETWORKS

The technological heterogeneity of R&D and knowledge interactions has been initially stressed in a sectoral systems of innovation context (see Malerba, 2002). In this conception, knowledge creation is considered as a non-linear and heterogeneous process, characterized by the specific interplay of actors and the technological knowledge they create, absorb and transmit across geographical space. In order to address these heterogeneities, several scholars proposed vital conceptualizations or taxonomies that enable distinguishing different “modes” of knowledge creation across fields and over time (see e.g., Jensen, Johnson, Lorenz, & Lundvall, 2007; March, 1991; Pavitt, 1984, 2005). Based on such conceptualizations, heterogeneities with respect to the specific rules, forms of interaction, or capabilities and resources predominant in specific domains, can be analytically disentangled and compared across scientific, technological or industrial fields (see e.g., Asheim, 2007; Moodysson, 2008). They are useful not only to determine fundamental characteristics, similarities or differences between fields but also to derive implications for the role of region-external R&D networks in each field.

In innovation economics, heterogeneities between technologies are usually investigated with respect to the complexity of knowledge combinations (Antonelli, 2011; Balland & Rigby, 2017; Fleming & Sorenson, 2001), the learning processes according to the nature of the knowledge base (Asheim, 2007; Moodysson, 2008), or the development stage of a technology and its relatedness to existing knowledge (Anderson & Tushman, 1990; Heimeriks & Boschma, 2014). Implicitly or explicitly, each approach may bear different indications for the predominant spatial structure and relevance of collaborative networks. For instance, based on the observation that the mobility of less complex knowledge is higher than of more complex knowledge as it requires less face-to-face communication and interaction (Sorenson, Rivkin, & Fleming, 2006), it would be reasonable to conclude that long-distance collaborations are less likely in fields characterized by a higher complexity in the knowledge creation process. Furthermore, the differentiation between “codified” and “tacit” elements in knowledge or technological development processes is also linked to the nature of knowledge (see e.g., Howells, 2002; Maskell & Malmberg, 1999). It is assumed that the degree of informal learning based on routines and experiences determines whether knowledge or distinct capabilities can be better transmitted locally or effectively travel long distances. This view suggests that more incremental modes of technological development, tied to the domestic industrial production processes, would favour localized knowledge exchange over region-external knowledge sourcing. However, if a technology or its underlying knowledge base is more explicit and has strong scientific elements, such as in biotechnology or nanotechnology (Bozeman, Laredo, & Mangematin, 2007;



Tamada, Naito, Kodama, Gemba & Suzuki, 2006), new, usually quite specific technological inputs are more often based on university research and drawn from selected partners located outside the region (Asheim, 2007). Hence, the role and spatial scale of R&D networks is likely to differ across technological fields, but a clear-cut answer is difficult to find in theory.

Recently, scholars started to take a dynamic perspective on the evolution of technologies and the role and structure of network linkages (Balland, Boschma, & Frenken, 2015; Ter Wal, 2013). Here, the evolution path of a technology or an industry can serve as an important conceptual vehicle for characterizing the different phases of development and with that the changing geographical patterns of collaboration and innovation. Generally, the spatial structure of collaboration is considered in a state of flux with advancing technological maturity. High uncertainty and need for frequent interaction may support geographically clustered R&D activities and collaboration in early stages of a technology, while a higher degree of standardization, the exploitation of dominant designs and diffusion of technologies may lead to geographically more dispersed linkages among actors in later stages of an industry or technology (Ter Wal, 2013).

Based on this discussion, it is reasonable to assume that knowledge creation effects of R&D network embeddedness depend on the technology under consideration. However, comprehensive investigations and studies allowing for comparisons on the role of networks in different technological fields are still missing. KETs, as applied in this study, provide a new inroad for the study of technological heterogeneities. Outstanding in the conception of the six KET fields is the degree of heterogeneity between them. The fields differ considerably in the predominant modes of knowledge creation (e.g., science-based vs. applied), the intuitional or organizational composition of important actors (e.g., university-related vs. SME), or in their interweaving with domestic industrial production structures. Hence, the technological fields referring to individual KETs serve as interesting starting point to dig deeper into the question of whether the general results, drawing a positive association between cross-regional R&D collaborations and regional knowledge creation, also hold for specific technologies. Potential differences between the technologies may be related to the debate on technological heterogeneities in R&D and differing knowledge creation modes.

3 | IDENTIFYING TECHNOLOGY-SPECIFIC R&D NETWORKS

At this point we describe the empirical strategy employed to observe the cross-regional R&D network activities disaggregated by KET fields. We use the KET classification to compare six different technologies in our comparative analysis of network effects on knowledge creation in European regions (see Section 4). This study covers a set of 257 NUTS 2 regions located in the EU 27 countries.

3.1 | Observing EU funded R&D networks in KET fields

The R&D networks we are interested in can be defined as a set of knowledge linkages between organizations jointly involved in a KET-specific research project funded by the EU-FP. Due to the funding requirements imposed by the FP, all projects involve—although to a different degree—cross-regional (cross-national) knowledge linkages. Data on FP projects is drawn from the EUPRO database, which contains basic information on the project (such as a duration, objective, etc.), the partners involved including the assignment to a NUTS 2 region, as well as the specific funding scheme and type of call under which the project was supported (Scherngell & Barber, 2009).² Since the projects are not pre-classified into technological fields, we queried the database and selected manually all KET-relevant projects. Given the industrial focus and time frame of this study, we restricted the search to cooperative R&D projects funded under FP7³ with a starting date in the period, 2007–2013.

²EUPRO is publicly available for research purposes within RISIS, an integrated research infrastructure for research and innovation policy studies (ris2.eu)

³All projects funded under the programmes "people", "ideas" and "capacities" were excluded from query. Furthermore, we exclude collaborative projects in the field of social sciences and related to the thematic area of "socio-economic sciences and the humanities."



To identify the relevant projects for the different fields, we reviewed in a first step the available project reports containing descriptions and definitional issues concerning the six KETs (Aschhoff et al., 2010; European Commission, 2015b). Based on this screening, we created a list of keywords (see Table A1 in Appendix A) containing the defining terms for each field. In a second step, we searched for these keywords in the project title, objective and project description, and assigned the relevant FP7 projects to KET fields. Finally, in a third step, we manually checked the obtained results of our queries and validated the assignment to the different fields. We browsed the project descriptions if necessary and deleted projects without a specific R&D goal (e.g., coordinative or support projects).

Based on the retrieved information, we came up with six different KET-specific R&D networks in which the nodes constitute the organizations interlinked due their joint project participation. Table 1 provides some basic SNA statistics measures from Social Network Analysis (SNA) on the different networks under consideration (see Wasserman & Faust, 1994 for a description of these measures). Although the size of the networks differs considerably, basic network characteristics such as density or average clustering are rather similar between the different KET fields. The largest network in terms of the participating organizations as well as the number of projects can be observed for photonics, while the smallest networks are the nanotechnology and microelectronics networks. The number of participating organizations and funded projects in photonics is, for instance, four times as high as in the nanotechnology network, although the ratio between organizations and projects is the smallest in photonics compared to all other KET networks. For all networks the share of linkages within a region is below 10%. Interestingly, the photonics network seems to be the most 'inclusive' as almost 90% of the European regions are included with at least one participating organization; in the microelectronics and nanotechnology networks, in contrast, only around 60% of regions are represented.

3.2 | Measuring regional embeddedness in technology-specific R&D networks

Given our interest in a region's embeddedness in KET related networks, we need to aggregate these organization level networks to the regional level. To calculate the region-level centrality variable, we follow the approach

TABLE 1 The KET networks: Descriptive statistics

	Nano- technology	Microelectronics	Photonics	Advanced materials	Advanced manufacturing technologies	Industrial biotechnology
Organizations (= nodes)	563	449	2,360	917	906	753
Projects	87	95	601	149	158	129
Edges	5,368	4,335	31,735	10,789	8,017	7,582
Av. degree	19.07	19.31	26.89	23.53	17.70	20.14
Max. degree	207	242	1,236	410	367	179
Std. dev. degree	17.22	23.29	49.17	28.73	18.19	19.98
Av. clustering	0.59	0.54	0.54	0.60	0.56	0.57
Network density	0.03	0.04	0.01	0.03	0.02	0.03
Share intra-regional linkages	6%	6%	7%	6%	7%	6%
Participating regions	63%	56%	88%	76%	74%	69%

Notes: Technology-specific networks are constructed at the organizational level. The regional sample consists of 257 European NUTS 2 regions. Degree denotes the number of links, namely, project participations, of an organization. Accordingly, Av. degree denotes the average degree of all organizations in the network, Max. degree the maximum number of participation, and Std. dev. degree the standard deviation of all degrees observed. Av. clustering is the average clustering of the organizations, namely, the share of closed triangles in the network, while network density denotes the ratio between the observed and the maximum possible number of links (see Wasserman & Faust, 1994 for a formal definition and further details). Participating regions refers to the share of regions with at least one participating organization in the networks.



introduced by Wanzenböck et al. (2015), calculating the degree centrality for each organization in each of the six KET fields, and in a second step aggregating these values for each of the 257 NUTS 2 regions based on the regional assignment of organizations. Non-participating regions are considered with a centrality value amounting to zero. The degree centrality is a local centrality measure that takes the number of network participations into account (Wasserman & Faust, 1994). We regard the degree centrality as the most useful indicator for reflecting a region's embeddedness in technology-specific R&D networks, given its simplicity of calculation and interpretation compared to other more complex global measures. Especially, for the marginal effects interpretation as employed in this study (see Section 5), degree centrality is the most useful centrality measure. The correlation among typical centrality measures is usually positive and high, in particular at the regional level of analysis (Valente, Coronges, Lakon, & Costenbader, 2008; Wanzenböck et al., 2015).

As a first exploratory step of the empirical analysis, Figure C1 (in Appendix C) illustrates the spatial distribution of the region-level degree centrality scores for each KET. Not surprisingly, we observe the “star” role held by the region of Ile-de-France (Paris), partly related to the quite centralized French research systems in contrast to, for example, Germany, as well as a strong dominance of the industrial core regions in Germany, France, Italy, Spain, and Scandinavia in all networks. However, we also see that degree centrality in industrial biotechnology, even though concentrated on Paris, is spread more equally among the remaining regions. In contrast, network centrality in microelectronics or nanotechnology, for instance, concentrates on a few hubs in Europe and is more unequally distributed over all regions.

4 | EMPIRICALLY MODELLING REGIONAL KNOWLEDGE CREATION

To estimate the impact of R&D networks on regional knowledge creation in KET fields, we build on an augmented regional knowledge production function (KPF) approach as introduced in Wanzenböck and Piribauer (2018), and regard the effects of R&D network embeddedness as dependent on other regional knowledge inputs.⁴ In this study, we provide measures to disentangle potential interaction effects of network embeddedness in a multiregional setting and to compare them between different technological fields.

Formally, the basic empirical model is given by:

$$Y_{ik} = \alpha + \beta X_{ik} + \gamma Z_i + u_{ik}, \quad (1)$$

where Y_{ik} represents the outcome variable denoting knowledge creation in region i in a specific KET field k , X_{ik} is a matrix of variables associated with a region's network embeddedness in a specific technological field, and Z_i a variable matrix reflecting other region-specific characteristics influencing regional knowledge creation. α denotes a constant, β and γ are respective response coefficients, and u_{ik} captures potential disturbances in our modelling relationship. The conditional dependence between network embeddedness and regional endowments is considered in form of:

$$X_{ik} = [c_{ik}, c_{ik} \times h_i], \quad (2)$$

⁴Key to the argument of including such an interaction relationship is the assumption that embeddedness in inter-regional R&D activities is driven by the skills or capabilities located within the region, determining the access and attractiveness in partnerships as well as the opportunities to exploit knowledge from external sources (Wanzenböck & Piribauer, 2018). Furthermore, own capabilities influence the importance of engaging in long-distance collaboration. While regions with own well-functioning innovation systems might be less dependent on external linkages, for them the challenge is rather to find the right type of knowledge or the right partner in light of limited relational capacities. The trade-off for regions having a strong internal knowledge base is rather that maintaining a large set of network relations demands resources and causes costs, while the benefits and learning effects of many relations might be relatively small.



where c_{ik} denotes the regions centrality in the KET-specific network as discussed in Section 3, and h_i denotes the skills and resources located within the region. Accordingly, the term $c_{ik} \times h_i$ reflects the interaction between these two variables.

To measure regional knowledge output Y_{ik} , we use the number of regional patent applications in different KET fields over the period from, 2009 to 2013. Patent data is based on patent applications filed to the EPO as derived from the OECD REGPAT database (March, 2016).⁵ In addition, we draw on the classification of Aschhoff et al. (2010) to assign the individual patent applications to KET fields based on the IPC codes listed on the patents (the list of IPC codes assigned to the KETs is provided in Table A2 in Appendix A). We use full counting and the location of the inventor to calculate the number of patent applications in a region. Figure C2 (in Appendix C) illustrates the skewed distribution of the patenting activity in KETs in our regional sample.

For our independent variables, we draw on the human resources (HR) in science and technology as provided by Eurostat. Data include all people which have completed tertiary education (ISCED 5-8) or are active in science and technology occupations as a percentage of the regional population. This indicator is used as proxy to capture the quality of human resources and technical skills in a region.⁶ Additionally, we calculate the share of intra-regional network linkages on all FP linkages in a specific KET field to include a control variable for domain-specific capabilities within a region. Accordingly, the variable can be considered as proxy for the relative inward orientation of regional linkages, suggesting the existence of a strong regional knowledge base or innovation system in a specific field. To control for more general regional characteristics (Z_i), we consider the intramural R&D expenditures in the business sector (in % of GRP) as a control variable to reflect the R&D intensity and financial R&D inputs of the domestic industries. Given the fact that KETs are technologies close to industrial manufacturing, the employment in the manufacturing sector (in % of the total employment) is used as additional proxy for the size of the industry sector in the region. A detailed description of all variables is provided in Appendix C.

We estimate a negative binomial (NegBin) regression model given the non-negative count data nature of our dependent variable, that is the number of regional patent applications. Furthermore, we follow recent works and apply an Eigenvector spatial filtering approach to remove the spatial dependence bias from the estimated parameters (Lata, Scherngell, & Brenner, 2015; Scherngell & Lata, 2013). Appendix B sets out the details of the Eigenvector filtering. The basic model of Equations (1) with (2) expressed as spatially filtered model version takes the form of:

$$E(Y_{ik}|X_{ik}, Z_i) = \exp \left(\beta_c c_{ik} + \beta_h h_i + \beta_{c \times h} (c_{ik} \times h_i) + \sum_{z=1}^Z \gamma_z Z_i + \sum_{m=1}^M \theta_m V \right), \quad (3)$$

where matrix V comprises M Eigenvectors of a first order contiguity spatial weights matrix serving as spatial filters. θ_m denotes the respective vector of coefficients for the spatial filters. As we are interested in technology-specific heterogeneities, we run individual regressions for the six KET fields under consideration.

5 | MARGINAL EFFECT MEASURES FOR THE ROLE OF R&D NETWORK EMBEDDEDNESS

The marginal effect of a variable—analytically defined as the partial derivative of the model—usually allows for comparison of the relative size and significance of the respective model parameters. In our case, however, both the interaction effect in the set of independent variables and the negative binomial model specification (Equation 3) induce non-linearities, which restricts direct interpretations of regression coefficients as they were marginal effects. The fact

⁵Note that we refrained from using granted patents only. First, we intend to proxy for knowledge creation activities in a region rather than the successful implementation, commercialization and application of this knowledge. Second, information on granted patents suffers from an immense time lag due to the duration of the granting process (2–10 years). This would invalidate the empirical setting of the current study.

⁶In contrast to our R&D network embeddedness variable, observations on the technology-specific skills are unfortunately not available for the 257 European NUTS 2 regions in our sample. We run robustness checks using data on the number of people with tertiary education (as a percentage of the active population), which delivered similar results for each of the KET specific models.



that adjustments are needed for interactions in non-linear models to correctly identify magnitude, sign and significance of the interaction effect has often been disregarded in applied econometrics (see e.g. the discussions in Ai & Norton, 2003; Greene, 2010; Karaca-Mandic, Norton, & Dowd, 2012; Tsai & Gill, 2013).

In this study, we make use of marginal effect calculations as introduced in Ai and Norton (2003). They derive appropriate marginal effect expressions for non-linear models with an interaction between two explanatory variables. Only in this way are we able to fully disentangle the effects of R&D network linkages from the presence of internal capabilities in a region, and in further consequence compare these (marginal) effects across the different KET fields. Important to note is that the usual interpretations associated with the marginal effect of an explanatory variable remain despite these adjustments. In our case that is: How much, on average, does the number of patents in a region change when network centrality increases (or any other independent variable) per one unit?

Following Equation (3), the *individual* marginal effect $\Theta_{(c_{ik})}$, here stated for a region's network embeddedness in a technology-specific network, on the conditional expected value of Y_{ik} can be expressed as:

$$\Theta_{(c_{ik})} = \frac{\partial E(Y_{ik}|X_{ik}, Z_i)}{\partial c_{ik}} = [\beta_c + \beta_{c \times h} h_i] E(Y_{ik}|X_{ik}, Z_i). \quad (4)$$

It is easy to see that the partial effect of c_{ik} in region i depends not only on the value of the interacted variable h_i but is also conditional on the expected value of Y_{ik} . Consequently, the marginal effects are not constant over the range of a variable, but depend on the value of all covariates in the model and are subject to variation across regions. All marginal effects are identified for each region as region-specific (or individual) marginal effect; the mean of these individual marginal effects gives us the average marginal effect for our regional sample (Ai & Norton, 2003). The individual marginal effect of a region's human resources are calculated in the same way as in Equation (4), with β_h being the main term and $\beta_{c \times h}$ the interacted term.

A similar argument as for the marginal effect of a main variable holds for the interpretation of the interaction term: As pointed out by Ai and Norton (2003), the interaction effect in non-linear models is neither the regression coefficient of the interaction term nor can it be simply computed by its marginal effect. In analogy to the marginal effects of a main variable, it is conditional on all independent variables, and thus, may even show different signs for different values of the covariates. Hence, we need to demarcate the effects induced only by the interacted variables (product-term induced interaction) from those effects induced by the value of other covariates (model inherent interaction) (Ai & Norton, 2003; Greene, 2010). For this study, the product-term induced interaction effects are of major interest as we aim at determining the conditional dependence between network embeddedness and regional skills in the generation of KETs. Formally, the product-term induced interaction effect, denoted as $I_{c \times h}$, can be expressed as the cross derivative of the expected value of Y_{ik} in terms of:

$$I_{c \times h} = \frac{\partial^2 E(Y_{ik}|X_{ik}, Z_i)}{\partial c_{ik} \partial h_i} = \frac{\Theta_{(c_{ik})}}{\partial h_i}, \quad (5)$$

measuring the change of the marginal effect of a region's network centrality when regional skills increase by one unit. Details on the estimation and asymptotics to identify the significance of the main term and the interaction effect are described in detail by Ai and Norton (2003).

Furthermore, when comparing KETs, we have to be aware of the fact that the marginal and interaction effects are not independent of the conditional expected value of Y_{ik} . The value of $E(Y_{ik}|X_{ik}, Z_i)$, and consequently also the magnitude of our effect estimates, depend on the range of the dependent variable, which is in our case highly determined by the patent intensity in a technological field. Without normalization, our marginal effect estimates for industrial biotechnology, for instance, would exceed the magnitude of those in all other fields simply due to the incomparably higher patenting intensity in this field. To achieve a measure that allows valid comparison across KET fields, we normalize the predicted counts for each region with the maximum in the respective KET before we calculate the marginal effects according to Equations (4) and (5).



6 | EMPIRICAL RESULTS

This section shifts attention to the estimation results of the models, specifically highlighting the mean and individual marginal effects estimates as described in the previous section, accompanied by some model diagnostics and a comparative interpretation between the KETs. We estimate six individual regression models for each KET according to Equation (3), with the coefficients and associated test statistics given in Appendix D. We perform Likelihood Ratio (LR) tests to check the robustness regarding the inclusion of the interacted variables (see Table D2 in Appendix D). For all models, the NegBin specification is confirmed statistically as shown by a significantly positive dispersion parameter.

In a second step, we calculated the marginal effects based on Equations (4) and (5). The results expressed in terms of averages of the region-specific estimates are presented in Table 2. Note that the displayed effect sizes of both the network centrality variable and the human resource variable (i.e., our interacted variables) refer to the total effects, as they incorporate the effects of the main term and the interacted term, calculated according to Equation (4). In our discussion, we focus first on the total effect of R&D network centrality on regional knowledge creation, and how the effect differs by KET, before we investigate the conditional dependence of regional network centrality and the human resources in more detail. For our remaining (control) variables we put forward only the most striking results.⁷

We find a significantly positive effect of network centrality on regional patenting intensity in all KET fields, confirming the positive influence of cross-regional networks on a region's invention potential as found in previous studies (see e.g., Ponds et al., 2010; Wanzenböck & Piribauer, 2018). These network effects, however, differ in strength depending on the specific technology under investigation. Mean marginal effects are particularly high in the field of nanotechnology, meaning that a one-unit increase in a region's network connectedness in the field of nanotechnology increases a region's patenting intensity in this field more than in other fields. For instance, the effect for Nanotechnology exceeds by more than double the amount we observe for Industrial biotechnology, the field with the second highest marginal effect on regional patenting. These results seem to reflect the importance of networks as mechanisms for knowledge flows—within as well as across regional borders—in more science-based industrial fields (see also the findings of Ponds et al., 2010). In contrast, the observed network effects are of relatively low value in the fields of advanced materials, advanced manufacturing technologies and microelectronics; fields that are typically linked more closely to industrial production, and knowledge generation is engineering-based and often more informal.

When we take a closer look at the spatial distribution of the individual marginal effects of network centrality for each region, we observe a rather unequal spatial pattern in all KET fields (Figure 1). The maps confirm that the network effects are higher in the traditional industrial core regions in Western Europe than in the peripheral regions in Southern, Central and Eastern Europe. Also in the spatial distribution of the network effects, differences between KET fields are noticeable: high network effects are more concentrated in the engineering-based fields of microelectronics, photonics or advanced manufacturing technologies, while they are more equally distributed across regions in the science-based sectors, in particular nanotechnology.

To get insights in the interrelation between R&D network centrality and region-internal human resources, we indicate the interaction effects calculated for our different KET models at the bottom of Table 2. Based on the product term induced interaction effects we can draw conclusions on direction and significance of the conditional dependence between region-external networks and region-internal endowments. Except for photonics, we observe small but significantly negative interaction effects for all models confirming the assumption that the availability of own-region endowments reduces the benefits arising from inter-regional networking, or a substitution effect between internal resources and external networks (see Wanzenböck & Piribauer, 2018).⁸ Generally speaking, the highest, or less negative, interaction effects can be found in Southern, Central and Eastern European regions (Figure D1 in

⁷While comparisons of effect sizes across fields are valid, comparisons across the independent variables need to be performed with caution and in light of how the respective variables are measured (in shares or absolute values).

⁸An alternative modelling approach to test the moderating effect of internal endowments would be to interact the network centrality with regional R&D expenditures, our proxy for regional R&D efforts and financial resources of firms. We tested this alternative specification for robustness and achieved similar results for all KET fields, confirming the presence of a substitution effect between region-internal resources and region-external knowledge sources.



TABLE 2 Mean of marginal effect estimates of the models with interaction

	Nanotechnology		Microelectronics		Photonics		Advanced materials		Advanced manufacturing technologies		Industrial biotechnology	
	Estimate	S.E.	Estimate	S.E.	Estimate	S.E.	Estimate	S.E.	Estimate	S.E.	Estimate	S.E.
Mean of marginal effects												
Network centrality	0.058	(0.006)	0.008	(0.002)	0.004	(0.002)	0.013	(0.002)	0.013	(0.002)	0.027	(0.003)
Human resources	0.138	(0.042)	-0.066	(0.057)	0.113	(0.014)	0.177	(0.075)	0.156	(0.021)	0.077	(0.120)
Business RD exp.	1.180	(0.144)	0.624	(0.231)	0.940	(0.387)	2.265	(0.319)	0.781	(0.136)	1.770	(0.203)
Empl in industry	-0.063	(0.008)	-0.018	(0.007)	0.145	(0.060)	0.256	(0.036)	0.193	(0.034)	0.038	(0.004)
Inward orientation	-0.264	(0.032)	0.120	(0.044)	0.076	(0.031)	0.363	(0.051)	0.096	(0.017)	0.202	(0.023)
Mean of interaction effect												
Product term induced	-0.009	(0.001)	-0.002	(0.001)	0.000	(0.000)	-0.003	(0.001)	-0.002	(0.000)	-0.008	(0.001)
Model inherent	0.009	(0.001)	0.001	(0.000)	0.000	(0.000)	0.003	(0.000)	0.002	(0.000)	0.007	(0.001)

Notes: Standard error (S.E.) in brackets; marginal effect calculation according to Equation (4) and interaction effect calculation according to Equation (5), both based on a Negative Binomial model specification including spatial filters (Equation (3)); model inherent interaction results from the interaction of all covariates produced by the non-linear negative binomial specification. The dependent variable is the number of regional patents in the respective field and expected count values are normalized by the maximum in each field to enable comparisons.

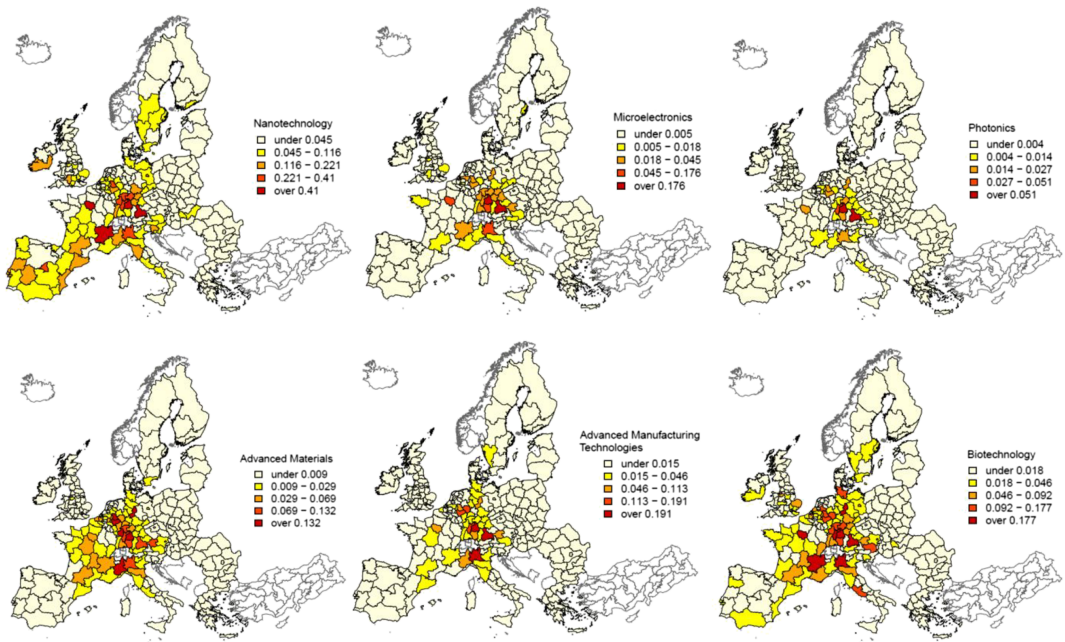


FIGURE 1 Spatial distribution of individual marginal effects of network centrality

Notes: Classification based on Jenks natural breaks. The spatial concentration of the effect of network centrality is confirmed by high Gini coefficients amounting to 0.86 for microelectronics and 0.77 for photonics, compared to 0.66 for industrial biotechnology and 0.62 for nanotechnology. Moran's I is significantly positive for all fields except nanotechnology.

Appendix D). Despite the higher network centrality effects in terms of magnitude in the Western European “core,” we see that the geographically more peripheral regions can generate *relatively* higher knowledge generation benefits from EU network participation. Concerning KET field-specific differences, the strongest interrelation with region-internal resources is identified for Nanotechnology and Industrial biotechnology. The fact that know-how in these fields is more generic or codified, thus less bound to on-site industrial production, as well as the operation of large research institutes and companies are potential explanations for the observed heterogeneities.

For our human resource variable, we find a positive effect on knowledge creation for almost all KET fields, which is well in line with previous empirical studies using a regional KPF approach at the aggregated level (e.g., Charlot, Crescenzi, & Musolesi, 2014; Paci, Marrocu, & Usai, 2014; Wanzenböck & Piribauer, 2018). Interestingly, a disaggregated KET-specific observation reveals that own skill endowments seem to have a relatively high influence on the engineering or production-based fields, advanced materials and advanced manufacturing, as compared to more-science based fields. For industrial biotechnology, the effects of region-internal skill endowments is even insignificant, in contrast to the effects of region-internal R&D expenditures and network centrality which are highly positive and significant.

Regarding other region-internal factors, the following findings are remarkable: In the field of Nanotechnology both a stronger industrial sector (measured by high industrial employment) and dense region-internal networks (measured by the number of intra-regional linkages) seem to negatively affect the inventive activity, while for all other fields these factors contribute positively to knowledge output. It further seems that region-internal and external networks are not as equally important for knowledge creation in the different KET fields. Both network-related variables seem to have a comparatively low effect in the advanced manufacturing technologies, while the effects of intra-regional networks are particularly high in the field of Advanced materials and Industrial biotechnology. Finally, all effect estimates—except for network centrality—show the highest significance in the field of Advanced materials. This finding



underlines the importance of the regional context in this field. Knowledge production in the material sector seems to be more closely related to the existing manufacturing sector in a region and driven by region-internal knowledge sourcing. The dominance of industry or application-oriented knowledge generation processes might explain why region-internal factors, in particular financial inputs of the business sector, seem to be more important for inventions in material research than in other fields.

7 | CONCLUSIONS

This paper investigates the role of regional embeddedness in EU funded R&D networks for the development of KETs in European NUTS 2 regions. With the notion of KETs, we bring technologies into focus that are a major building block of industrial and innovation policy strategies at EU level as well as in countries or regions. Given the horizontal and systemic nature of KETs, developing capabilities is considered crucial for regions to create new innovation and growths paths, with high potential for cross-sectoral or cross-regional spillovers (Evangelista et al., 2018; Montresor & Quatraro, 2017). Local and global knowledge networks might play a pivotal role in the generation of KETs, particularly as they are widely recognized as a major vehicle of knowledge spillovers (see e.g., Breschi & Lissoni, 2001; Owen-Smith & Powell, 2004). However, it is not clear which role the regional network conditions play for the heterogeneous technologies, and whether high inter-regional interconnectivity can stimulate the building of regional capabilities in such key fields.

The aim of our study was twofold: first, contributing to the scarce regional literature on KETs by providing new evidence on the regional determinants of the development of KET capabilities, in particular on effects of a region's embeddedness in EU-wide networks; second, systematically comparing the impact of regional network embeddedness across different KET fields in light of the different knowledge bases, dominant modes of knowledge production or spatial network structures characterizing these technological fields. Our empirical model is based on the assumption that the significance of network effects is interrelated with a region's resources and skill endowments. We relied on an augmented regional knowledge production function (KPF) approach as in Wanzenböck and Piribauer (2018) to account for such interaction effects, and introduced marginal effect interpretations applicable for non-linear model specifications. We estimated a spatially filtered negative binomial regression model based on which we derive average marginal effects to quantify and compare the impacts of R&D network embeddedness across technological fields.

Our technology-specific analysis confirms the results found by Wanzenböck and Piribauer (2018) supporting the assumptions of a generally positive role of network embeddedness for domestic knowledge generation, on the one hand, and the *relatively* decreasing importance of inter-regional networks for regions with high own endowments, on the other hand. Building on these two relationships, the study delivers three main novel insights regarding technology-specific aspects:

First, the positive role of regional network embeddedness clearly differs between individual technological fields, being particularly significant for knowledge generation in science-based technological fields. This finding is well in line with previous observations that both nanotechnology and industrial biotechnology draw heavily on scientific inputs, often organized in form of collaborations of inter-regional, or even inter-national scale (Bozeman et al., 2007; Heimeriks & Boschma, 2014; Owen-Smith & Powell, 2004; Ter Wal, 2013). In contrast, the influence of network embeddedness is lower in fields linked more closely to industrial and on-site production processes, where knowledge generation processes are typically more informal and engineering-based (European Commission, 2015a). Network linkages, both region-internally and region-externally, seem to be of low significance for the development of advanced manufacturing technologies.

Second, the interdependence between region-external networks and region-internal resources seems to be stronger for knowledge generation in nanotechnology and industrial biotechnology. This finding suggests that knowledge sourcing via inter-regional networks can particularly in the science-related fields act as a substitute for lower levels of own regional skills. Given the codified, more explicit, nature of the knowledge base, close network linkages to other



regions may help lagging regions to develop technological capabilities in these fields. In contrast, the development of new technologies in application-oriented fields, in particular in the case of advanced materials, seems to be mainly driven by region-internal knowledge production conditions.

Third, interesting from a pan-European perspective is the finding that we observe noticeable differences in the spatial distribution of the regional network effects. While network effects are more spatially concentrated in the engineering-based fields of microelectronics, photonics or advanced manufacturing technologies, the benefits of inter-regional network linkages seem to be more equally distributed across regions in the science-based sectors. However, in any case the effects of EU funded R&D networks are higher in the “industrial core” regions of Western Europe. It therefore seems as EU funded projects reinforce a highly unequal regional distribution of KET capabilities.

Some limitations and, accordingly, ideas for future research come to mind. By limiting to the case of EU funded R&D networks, we are aware that we analyse a specific, policy-driven type of knowledge networks, which limits the generalizability and transferability of results. Moreover, the classification of KETs is not untainted by problems typically arising from the application of broad typologies, such as a high in-class variety. At the same time, however, this study is to the best of our knowledge the first European-wide one that systematically considers technological heterogeneities in cross-regional network structures. A valuable extension would be to further account for organizational or institutional differences, or the location of key organizations such as universities or important research organizations, in the cross-regional networks. Moreover, the evolution of policy-induced networks over time, or their effects on innovation and the successful development of new products and processes at the regional level would be a crucial point for further analyses. This also relates to questions of whether investments in generic or key technologies can lead to or leverage the comparative advantages of regions in certain sectors or fields, such as with regional smart specialization strategies (Foray, David, & Hall, 2009; Montresor & Quatraro, 2017). In this regard, our study clearly points to technology-specific pathways which are idiosyncratic with different regional drivers.

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APPENDIX A

OBSERVING KEY ENABLING TECHNOLOGIES

TABLE A1 List of Keywords for retrieving KET-specific networks

KET	Keywords
Nanotechnology	nanotechnology, nanoelectronics, nanomaterials, nanoanalytics, nanotools, nanoinstruments, nanomeasuring, nanooptics, nanomagnetism, nanostructures
Microelectronics	semiconductors, microelectronics, nanoelectronics
Photonics	solar, "lighting" ^a Und Wie "aphotonic," "laser" ^a Und Wie "aphotonic," optical, sensor, "lens" ^a Und Wie "aphotonic"
Advanced materials	advanced metal, advanced polymer, advanced ceramic, superconductor, composite, biomaterial, advanced material, smart material
Advanced manufacturing technologies	robotics, industrial process, machine tools, computer-integrated, automation, computer integrated, transportation technology, logistic technology, computing technology, measuring technology, measurement technology, manufacturing technology
Industrial biotechnology	enzyme, fermentation, biochemical, biomaterial, "biotechnolog" ^a Und Wie "industrial" ^a

Note: ^aall FP7 projects not in: ERC, SSH, SME, PEOPLE, REGION, INFRASTRUCTURE, SIS, REGPOT.



TABLE A2 List of IPC classes of KET fields (based on Aschhoff et al., 2010)

KET	IPC
Nanotechnology	Y01N, B82B
Microelectronics	H01H 57/7, H01L, H05K 1, H05K 3, H03B 5/32, Y01N 12
Photonics	F21K, F21V, G02B 1, G02B 5, G02B 6, G02B 13/14, H01L 25/00, H01L 31, H01L 51/50, H01L 33, H01S 3, H01S 4, H01S 5, H02N 6, H05B 31, H05B 33
Advanced materials	B32B 9, B32B 15, B32B 17, B32B 18, B32B 19, B32B 25, B32B 27, C01B 31, C04B 35, C08F, C08J 5, C08L, C22C, D21H 17, H01B 3, H01F 1, H01F 1/12, H01F 1/34, H01F 1/44, Y01N
Advanced manufacturing technologies	B03C, B06B 1/6, B06B 3/00, B07C, B23H, B23K, B23P, B23Q, B25J, G01D, G01F, G01H, G01L, G01M, G01P, G01Q, G05B, G05D, G05F, G05G, G06M, G07C, G08C, co-occurrence of G06 and any of A21C, A22B, A22C, A23N, A24C, A41H, A42C, A43D, B01F, B02B, B02C, B03B, B03D, B05C, B05D, B07B, B08B, B21B, B21D, B21F, B21H, B21J, B22C, B23B, B23C, B23D, B23G, B24B, B24C, B25D, B26D, B26F, B27B, B27C, B27F, B27J, B28D, B30B, B31B, B31C, B31D, B31F, B41B, B41C, B41D, B41F, B41G, B41L, B41N, B42B, B42C, B44B, B65B, B65C, B65H, B67B, B67C, B68F, C13C, C13D, C13G, C13H, C14B, C23C, D01B, D01D, D01G, D01H, D02G, D02H, D02J, D03C, D03D, D03J, D04B, D04C, D05B, D05C, D06B, D06G, D06H, D21B, D21D, D21F, D21G, E01C, E02D, E02F, E21B, E21C, E21D, E21F, F04F, F16N, F26B, G01K, H05H
Industrial biotechnology	C02F 3/34, C07C 29/00, C07D 475/00, C07K 2/00, C08B 3/00, C08B 7/00, C08H 1/00, C08L 89/00, C09D 11/04, C09D 189/00, C09J 189/00, C12M, C12N, C12P, C12Q, 12S, G01N 27/327 (excl.co-occurrence with A01), A61, C12N, C12P C12Q

APPENDIX B

EIGENFUNCTION SPATIAL FILTERING

LeSage, Fischer, and Scherngell (2007) point out that the heterogeneity term introduced in the negative binomial specification is not able to account for the spatial bias introduced via spatial dependence of the dependent variable. Hence, estimation of a standard NegBin model may be biased due to the presence of spatial dependence across spatial units, violating the independence assumption of the negative binomial model (Chun, 2008). A natural way to deal with the spatial dependence issues would be to use standard spatial autoregressive techniques, specifying a spatial Durbin model and testing for different kinds of spatial dependence. However, standard spatial autoregressive techniques can hardly be applied given the distributional assumptions of our dependent variable (LeSage et al., 2007). Thus, since our prime interest lies in estimating our parameters β_c , β_h and $\beta_{c \times h}$ consistently (i.e., we are not interested in spatial spillover effects *per se*), we follow recent works by applying an Eigenfunction spatial filtering approach to remove the spatial dependence bias from the estimated parameters (Lata, Scherngell and Brenner, 2015; Scherngell & Lata, 2013). Its main advantage is that it can be applied to any functional forms (see Patuelli, Griffith, Tiefelsdorf, & Nijkamp, 2011) and does not depend on the normality assumption.

The essence of the Eigenfunction spatial filtering approach is to extract Eigenvectors as spatial surrogates from a spatial weights matrix C , given by:

$$C = \left(I - \frac{1}{n} \mathbf{1} \mathbf{1}^T \right) W \left(I - \frac{1}{n} \mathbf{1} \mathbf{1}^T \right), \quad (5)$$

where W denotes a row-standardized n -by- n first order contiguity matrix, I the n -by- n identity matrix, and $\mathbf{1}$ a n -by-1 vector of ones. As mathematically derived by Griffith (1996), each extracted Eigenvector V_i relates to a specific map



pattern featuring a certain degree of spatial autocorrelation, while at the same time the full set of Eigenvectors V_n describes the full range of all possible mutually orthogonal and uncorrelated map patterns (Scherngell & Lata, 2013).⁹

Adding these Eigenvectors to our model as additional independent variables assigns them their intended role as spatial filters, isolating spatial dependence effects from the remaining estimates. In order to avoid overfitting problems, we follow Fischer and Griffith (2008) and add not the full set of Eigenvector to our model to be estimated, but only the relevant ones showing a certain degree of spatial dependence. We measure the degree of spatial dependence by means of the Moran' I test, and include 58 Eigenvectors.

APPENDIX C

DESCRIPTIVES FOR THE VARIABLES

TABLE C1 Description of variables

Variable	Definition	Source
Regional knowledge creation in a specific KET field (dependent variable)	Number of patent applications filed to the EPO in a KET field according to IPC codes (Aschhoff et al., 2010); full counting based on inventor address, mean 2009–2013	OECD REGPAT database
Network centrality	Sum of the degree centralities of organizations located in a region; calculated for KET-specific networks based on projects funded by the 7th Framework Programme (FP7) from 2007 to 2013.	EUPRO database
Inward orientation	Number of intra-regional network linkages; in % of the total number of linkages. Calculated for KET-specific networks based on projects funded by the 7th Framework Programme (FP7) from 2007 to 2013.	EUPRO database
Human resources	Regional population (25–64y) with tertiary education (ISCED 5–8) or employed in a S&T occupation, in % of total regional population, mean, 2007–2013	Eurostat regional statistics
Business RD expenditures	Intramural R&D expenditures of the business enterprise sector (BES), in % of GRP, mean, 2007–2013	Eurostat regional statistics
Employment in industry	Regional employment in the manufacturing sector, in % of total regional employment, mean, 2008–2013	Eurostat regional statistics

⁹See Griffith (2003) for further details on the characteristics of the extracted Eigenvectors.

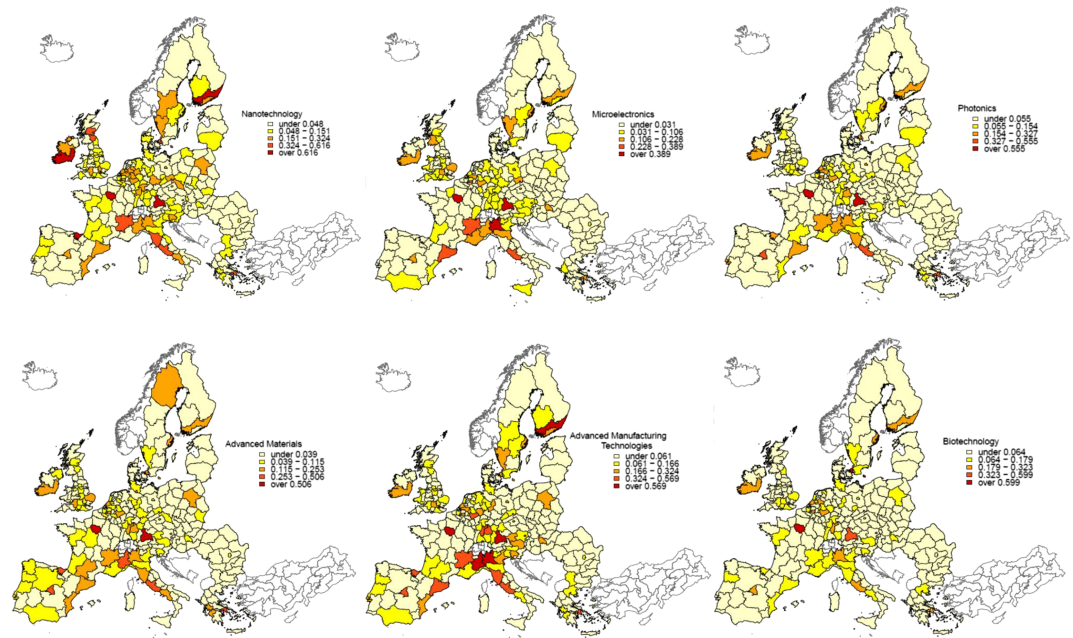


FIGURE C1 Spatial distribution of degree centrality in each KET field
Notes: Regional centrality values are normalized between 0 and 1 for each field. Classification based on Jenks natural breaks.

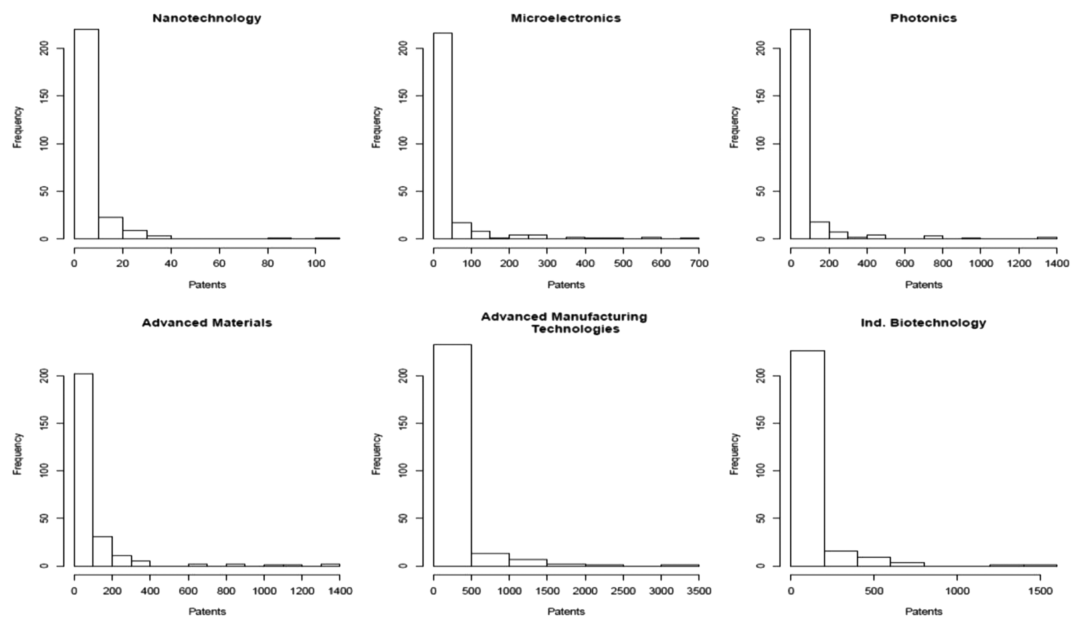


FIGURE C2 Distribution of the number of regional patents in each KET field

APPENDIX D

REGRESSION RESULTS



TABLE D1 Regression results for negative binomial models with interaction effect

	Nanotechnology		Microelectronics		Photonics		Advanced materials		AMT		Industrial biotechnology	
	coeff.	S.E.	coeff.	S.E.	coeff.	S.E.	coeff.	S.E.	coeff.	S.E.	coeff.	S.E.
Centrality	0.025	0.006***	0.016	0.005***	0.002	0.001***	0.007	0.002***	0.008	0.002***	0.016	0.002***
HR	0.072	0.023***	0.046	0.017***	0.069	0.016***	0.078	0.015***	0.086	0.013***	0.088	0.013***
Network × HR	0.000	0.000***	0.000	0.000**	0.000	0.000**	0.000	0.000***	0.000	0.000***	0.000	0.000***
RD exp.	0.242	0.132*	0.543	0.112***	0.287	0.104***	0.409	0.104***	0.251	0.088***	0.347	0.086***
Empl. in ind	-0.013	0.025	-0.016	0.019	0.044	0.016***	0.046	0.015***	0.062	0.013***	0.007	0.014
Inward Links	-0.054	0.041	0.105	0.030***	0.023	0.018***	0.066	0.029**	0.031	0.022	0.040	0.020**
Spatial filters	yes		yes		yes		yes		yes		yes	
Dispersion	0.740	0.113***	0.623	0.072***	0.536	0.054***	0.508	0.050***	0.789	0.117***	0.413	0.042***
Model fit												
Log lik	-521.788		-825.953		-1030.512		-1085.359		-1283.259		-526.140	
Mc Fadden's R2	0.182		0.203		0.175		0.172		0.175		0.175	
AIC × n	1175.575		1783.905		2193.024		2302.719		2698.519		2419.330	
BIC	122.776		-64.658		-82.718		-96.768		-138.287		-100.166	

Notes: Negative binomial Regression incl. spatial filters; dependent variable is the number of regional patents; S.E. = Standard error; AMT = Advanced manufacturing technologies.



TABLE D2 Regression results for negative binomial models without interaction effect

	Nanotechnology		Microelectronics		Photonics		Advanced materials		AMT		Industrial biotechnology	
	coeff.	S.E.	coeff.	S.E.	coeff.	S.E.	coeff.	S.E.	coeff.	S.E.	coeff.	S.E.
Centrality	0.010	0.002***	0.006	0.002***	0.001	0.000***	0.002	0.001***	0.004	0.001***	0.003	0.001***
HR	0.049	0.022**	0.036	0.017**	0.056	0.015**	0.061	0.014***	0.074	0.012***	0.071	0.014***
RD exp	0.332	0.136**	0.570	0.113***	0.326	0.105***	0.439	0.107***	0.268	0.090***	0.436	0.093***
Empl. in ind.	-0.008	0.025	-0.012	0.019	0.045	0.016***	0.049	0.016***	0.065	0.013***	0.014	0.015
Inward Links	-0.060	0.041	0.108	0.031***	0.029	0.018	0.060	0.030***	0.035	0.023	0.053	0.022**
Spatial filters	yes		yes		yes		yes		yes		yes	
Dispersion	0.789	0.117***	0.637	0.073***	0.548	0.055***	0.529	0.052***	0.435	0.041***	0.469	0.046***
Model fit												
Log lik	-526.140		-828.288		-1033.768		-1090.140		-1287.157		-1158.507	
Mc Fadden's R2	0.175		0.200		0.173		0.169		0.159		0.155	
AIC × n:	1182.281		1786.577		2197.535		2310.280		2704.315		2447.015	
BIC:	125.932		-65.536		-81.756		-92.756		-136.040		-76.031	
LR Test (models with vs. without interaction)	8.710	0.003	4.670	0.031	6.510	0.011	9.560	0.002	7.800	0.005	29.680	0.000

Notes: Negative binomial regression incl. spatial filters; dependent variable is the number of regional patents; S.E. = Standard error; AMT = Advanced manufacturing technologies.



TABLE D3 Spatial autocorrelation and concentration of individual network centrality effects

	Gini	Moran' I
Nanotechnology	0.62	0.04
Microelectronics	0.86	0.18***
Photonics	0.77	0.29***
Advanced materials	0.75	0.37***
Advanced manufacturing technologies	0.75	0.25***
Industrial biotechnology	0.66	0.36***

Notes: Moran' I and Gini coefficient are calculated on the basis of the individual marginal network effects. *** significant at the 0.01 level.

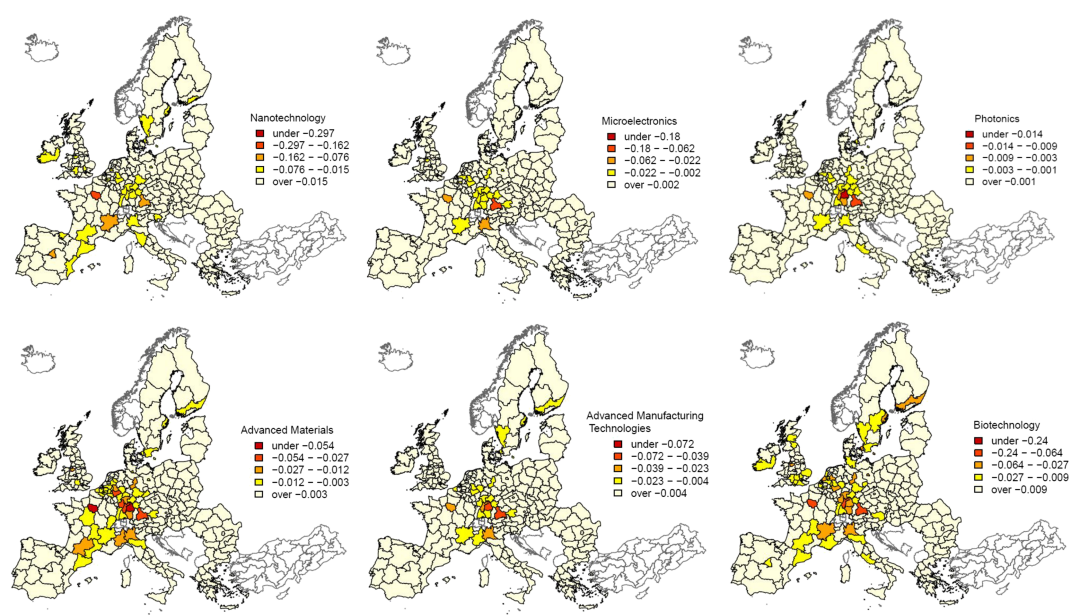


FIGURE D1 Spatial distribution of the region-specific interaction effects (natural breaks)
Notes: Classification based on Jenks natural breaks.



Resumen. Las redes interregionales de I+D son esenciales para la innovación regional. Sin embargo, se carece de conocimientos sobre los efectos específicos del campo de la tecnología en la conectividad de la red de una región. Este estudio investiga las tecnologías facilitadoras clave (TFC) para comparar los efectos de la creación de conocimientos de las redes de I+D financiadas por la UE para diferentes campos tecnológicos. Se cuantifican y comparan los efectos de red a través de los campos TFC mediante la aplicación de modelos de regresión filtrados espacialmente junto con interpretaciones de efectos marginales para modelos no lineales. Los resultados muestran que los efectos de red generalmente positivos difieren en función de las dotaciones internas de la región y de la naturaleza de las tecnologías subyacentes. Las implicaciones políticas se derivan de las interrelaciones entre la investigación de la UE y su política industrial y regional.

抄録: 地域におけるイノベーションの活性には、地域間の研究開発ネットワークが不可欠である。しかし、技術分野に特異的な地域ネットワークのつながりに関する理解が欠如している。本稿では、欧州連合 (EU) の出資による様々な技術分野における研究開発ネットワークの知識創造効果との比較により、KET (Key Enabling Technology: 実現可能にする重要な技術) を検討する。非線形モデルによる限界効果の分析に合わせて空間フィルターを実行する回帰分析モデルを用いて、KET 分野全体におけるネットワーク効果の定量化と比較を行う。プラスのネットワーク効果は、概して、地域内部の資本と基礎にある技術の性質によって異なることが結果から示される。EU における調査研究、産業政策と地域政策の相互関係に政策的インプリケーションが生じる。